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How to Say No in Recognition Tests of Visual Working Memory: Testing Unidimensional and Two-Dimensional Models with Continuous or Discrete Memory States

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Abstract

We constructed four working memory recognition models to predict behavior in the Local Recognition task (a.k.a. Change Detection), in which both content (e.g., color) and context (e.g., location) information are necessary to make correct recognition decisions. The theoretical assumptions incorporated in the models come from crossing two contrasts: One is the contrast between Discrete-State models with Continuous-Strength models. The other contrast pertains to the dimensionality of information involved in the recognition process: either Unidimensional (as in single-process recognition models) or Two-Dimensional (as in dual-process models). We compared the models to data from three local-recognition experiments using sequentially presented visual materials. All three experiments revealed intrusion costs (i.e., higher false alarms to probes matching a list element in the wrong context than to new probes) and U-shaped serial-position curves for all probe types. The Two-Dimensional Continuous-Strength model predicted these results best both qualitatively and quantitatively. The Unidimensional and Two-Dimensional Discrete-State models were able to predict the qualitative pattern of serial-position curves but failed to predict a sufficient amount of intrusion cost. The Unidimensional Continuous-Strength model failed even to predict the qualitative pattern of the serial position effects.

Keywords: working memory; recognition; dual-process models; Discrete-State models; Continuous-Strength models

How to Say No in Recognition Tests of Visual Working Memory: Testing Unidimensional and Two-Dimensional Models with Continuous or Discrete Memory States

Since the seminal studies of Sternberg (1966), short-term recognition tasks have played a major role in studying short-term or working memory. A long tradition of research following Sternberg has aimed to investigate the cognitive processes underlying recognition (Donkin & Nosofsky, 2012; Kahana & Sekuler, 2002; D. J. Mewhort & Johns, 2000). Theoretical approaches in this tradition are divided between single-process theories (Brockdorff & Lamberts, 2000; Kahana & Sekuler, 2002; D. J. K. Mewhort & Johns, 2003; Nosofsky, Little, Donkin, & Fific, 2011) and dual-process theories of short-term recognition (Atkinson, Hermann, & Wescourt, 1974; Göthe & Oberauer, 2008; Oberauer & Lange, 2009). More recently, the recognition paradigm has resurfaced under the label of "change detection" in the literature on visual working memory, where it plays a role in the debate on the nature of short-term memory capacity. Although the debate is multi-faceted (Suchow, Fougnie, Brady, & Alvarez, 2014), the main theoretical rift is between proponents of discrete capacity (Luck & Vogel, 1997; Rouder et al., 2008) and proponents of a continuous resource (Bays & Husain, 2008; Wilken & Ma, 2004). Here we cross-fertilize the two research traditions and test four mathematical models. The theoretical ideas implemented in these models were form a factorial combination of single- and dual-process theories with discrete or continuous limitations on working memory capacity. We test those models on serial-positon effects and the intrusion cost in the local recognition task (see next session for detail). In the following we introduce the procedure of the local recognition task, and then explain the contrast between single- and dual-process theories -- which we re-frame in terms of recognition using unidimensional or two-dimensional information from memory -- and the contrast between discrete and continuous models of working memory capacity. We then introduce mathematical formalizations of four models. Each of the models was designed to represent one cell of the design crossing the two theoretical contrasts in such a way that it gives the theoretical idea in that cell a good chance to succeed. As we explain below, this made it necessary to make specific implementation decisions for each model, so that the models represent a factorial 2 x 2 design on the level of the theoretical ideas they represent but not in terms of their mathematical form.

The Local Recognition Task

The models introduced in this study are designed for predicting the data from local recognition tasks. Therefore, we introduce the experimental paradigm before introducing the models. The experimental procedure is similar to the procedure used in Oberauer (2008), except that the stimuli were changed from verbal to visual materials to be in line with the change detection task. In Experiment 1, we used Chinese characters as stimuli for non-Chinese speaking participants. In Experiments 2 and 3, we used color patches as material, with different schemes of stimulus selection (as described in a later section). Both Chinese characters and colors are commonly used in change-detection task, and we tested both in our experiments to ensure that our results can be generalized.

The procedure is shown in Figure 1. At the beginning of each trial, five empty frames were presented on the screen indicating the possible location of the items. Five items were then presented sequentially in different locations from left to right. After all the items were presented, a probe appeared in one of the locations, selected at random. Participants were instructed to judge if the probe is the same as the item presented in that location. There are three types of probe in local recognition tasks: *Positive* probes, *new* probes, and *intrusion* probes. A positive probe is the same as the content presented in the probe location. Participants were instructed to accept positive probes. A new probe does not match any of the contents presented in the current trial. Participants were instructed to reject new probes. An intrusion probe matches one of the contents in the memory list but is presented at a different location. Participants were instructed to reject intrusion probes.

Comparing to the typical recognition task, the local recognition task does not only require participants to remember if the probe is in the memory list, the participants also have to remember if the probe is presented in its original location. Thus, participants have to keep in memory both the content information (i.e., which visual stimuli have been presented) and the context information (i.e., which stimulus has been in which location). This makes the experiments suitable for investigating the potential process(es) of integrating two sources of information: Memory for the contents of the current memory set, and memory for content-context bindings. Results from local recognition tasks show an *intrusion cost*, that is, intrusion probes are more difficult to reject than new probes (Oberauer, 2001, 2003). The intrusion cost reflects the conflict between the two sources of information, and as such it is diagnostic for the question we discuss next: How are these two sources represented, and how are they used in recognition?

Unidimensional Versus Two-Dimensional Models

The unidimensional view assumes that all the information extracted from memory in response to a recognition probe is integrated into one single variable which affects the recognition process. This variable reflects the degree of match between the probe and one or several representations in memory – either as a continuously varying signal, or as a discrete state of detecting (or not) a match. The Two-Dimensional view assumes that two sources of information from memory are used separately in the recognition process. Typically, one source provides the item information, reflecting whether the probe matches an item of the current memory set. The extraction of item information is often described as *familiarity* process in dual-process theory. Another source provides binding information between item and context in memory, for instance the binding between a spatial location and an item. Accessing bindings between item and context information is described as *recollection* process in dual-process theory. It is important to note that two-dimensional models do not necessarily assume two recognition processes. In a two-dimensional model, the two sources of information – item information and binding information – vary independently along two dimensions of strength or availability (Rotello, Macmillan, & Reeder, 2004; Wixted & Mickes, 2010). As a consequence, in two-dimensional models, item information and binding information can fail independently, whereas in uni-dimensional models, this is not possible. In the following we will describe two-dimensional models as involving two processes, familiarity and recollection, which access the two sources of information, respectively, but we do this only for convenience, not implying a commitment to two qualitatively different processes (for further discussion of the distinction of processes in recognition see Oberauer, 2018).

In the unidimensional view, the intrusion cost is explained through the partial match between the probe representation and the memory representations (Brockdorff & Lamberts, 2000). The item and its location form one episode which is stored as such in memory. At test, the memorized episodes are compared to the episode of the probe, which also consists of the probe item together with its location. A new probe is easy to reject because it only has a partial match – with regard to the location – to one of the episodes in memory. An intrusion probe is harder to reject because it has two partial matches with two episodes in memory – with one it shares the location, and with another it shares the item. Therefore, the summed similarity of the probe episode to all episodes in memory is higher for an intrusion probe than a new probe.[1]

In Two-Dimensional models, the intrusion cost is explained through the conflict between item information (i.e., familiarity) and item-context binding information (i.e., the outcome of recollection). The item information can only assess the memory strength of item representations matching the probe, regardless of their context (i.e., their location). Thus the item information favors a *no* response towards a new probe, because the new probe did not appear during study, and hence has low memory strength. However, the familiarity process cannot distinguish an intrusion probe from a positive probe, because for both there is one item in the memory set matching the probe. Therefore, the item information favors a *yes* response to an intrusion probe. In contrast, recollection can provide information about which item has been presented in which location. Recollection can rely on two directions of retrieval, referred to as Recollection 1 and Recollection 2 (Oberauer, 2008). Recollection 1 uses the probe's context (i.e., its location) as a retrieval cue to retrieve the content (i.e., the item) bound to it. In case of an intrusion probe, the retrieved content mis-matches the content of the probe, so that the probe can be rejected. Recollection 2 uses the probe's content as retrieval cue to access its context. In case of an intrusion probe, this means to retrieve the *position of origin* of the probe – the location in which it has been presented in the memory list. This location mis-matches the location of the probe, again enabling rejection of the probe. Regardless of which recollection route retrieves item-context bindings, in order to make a correct response to an intrusion probe, the recollected item-context information has to override the item information reflected in familiarity, because the item information and the information on item-context bindings provide opposing response tendencies towards intrusion probes. This conflict explains the intrusion cost.

Although both the unidimensional view and the Two-Dimensional view are able to explain the intrusion cost, they can be distinguished through their qualitatively different predictions for serial position effects. Oberauer (2008) derived differential predictions of the two theories through mathematical modeling. By creating mathematical models for both theories, both models make explicit predictions that can be compared quantitatively and qualitatively. According to the models developed in Oberauer (2008), the unidimensional (a.k.a. single-process) model predicts that the serial-position curves for accuracies and response times for intrusion probes in local recognition must have a mirror-reversed shape compared to those for positive probes. In contrast, the dual-process model predicts that the serial-position curves of intrusion probes and positive probes must be parallel. The results were in favor of the dual-process model. The predicted serial-position curves from the dual-process model matched the observed serial-position effects better than the single-process model.

Discrete Slots versus Continuous Resources

The local recognition task is also used in visual short-term memory studies, where it is called single-probe change-detection task. In the single-probe change-detection task, an array of visual stimuli is presented during the study phase. At test a single probe appears at the same location as one of the previously studied items. Participants are asked to detect if the probe has changed between study and test. The findings from single-probe change-detection task match those from the local recognition task: A change using an intrusion probes (i.e. the probe is part of the memory array but presented in the wrong location) is harder to detect than a change by introducing a new probe that has not been in the array at all (Donkin, Tran, & Le Pelley, 2015; Rerko & Oberauer, 2013).

Much of the research using the change-detection task has been devoted to adjudicate between discrete-capacity and continuous-resource models of visual working memory capacity. The discrete-capacity or slot model assumes that working memory consists of a discrete number of slots, and a slot can hold only a single object (i.e., a single array item together with its location). Thus a working memory with K slots can only hold K objects at a time. If the number of objects in an array exceeds K, the objects not stored in the slots are not represented in memory at all. When set size increases, the chance of an individual object to be stored decreases accordingly. As a result, performance decreases when the set size increases. By contrast, the resource model assumes that working memory has a limited amount of resource, which can be distributed among all objects. Because the resource is a continuous quantity that can be divided into infinitely small portions, there is no limit on the number of objects stored in working memory. However, the quality of memorized objects is affected by the amount of resource assigned to the object. When set size increases, the resource share of each object decreases, thus performance decreases accordingly.

Both slot models and resource models of change detection have so far relied on unidimensional, single-process assumptions about the recognition process in change detection. In discrete-capacity models, an object is either remembered with at least the quality afforded by one slot or forgotten entirely. Therefore, discrete-capacity models imply that the cognitive system enters one of two discrete states at test: Either it remembers the tested object (i.e., the array item in the probed location), in which case the change decision can be made with high accuracy as long as the change is reasonably large (which it typically is in change-detection experiments), or it remembers nothing about the tested object, in which case it can only guess. This Discrete-State model of the recognition decision is known as the two-high-threshold model. Empirical support for the threshold model of change detection has been interpreted as support for the Discrete-State model of memory (Rouder et al., 2008). In contrast, in continuous-resource models an object is never forgotten entirely, but the quality of its representation is continuously degraded as its resource share is reduced. The information from memory in favor or against a *change* response arguably reflects the representational quality of the tested object: The lower its quality, the weaker (i.e., more ambiguous) the retrieved information. When memory information varies on a continuous dimension of strength, the recognition decision is usually modeled by a variant of signal-detection theory (SDT). Accordingly, formalizations of continuous-resource models of change detection have mostly relied on signal-detection decision processes (van den Berg, Shin, Chou, George, & Ma, 2012; Wilken & Ma, 2004). Critically for the present context, both two-high-threshold models and SDT models are instances of single-process or unidimensional models of recognition.

According to Oberauer (2008), single-process models should have difficulty to explain the serial-position effects of different probe types in the local recognition task. However, Oberauer (2008) considered only SDT versions of unidimensional and Two-Dimensional models. Here we test the full combination of unidimensional and Two-Dimensional models with SDT and two-high-threshold models. Moreover, Oberauer (2008) tested local recognition memory with verbal materials only. Therefore, here we tested local recognition with visual material in order to bring our experiments more in line with single-probe change-detection tasks.

Models

In the following section we present four formal models for the local recognition task: a Unidimensional Discrete-State model, a Two-Dimensional Discrete-State model, a Unidimensional Continuous-Strength model, and a Two-Dimensional Continuous-Strength model. The Unidimensional Continuous-Strength model and the Two-Dimensional Continuous-Strength model are adapted from Oberauer (2008). The Unidimensional Discrete-State model is adapted from the classic slot model with modifications to simulate the swap error and the serial-position effect in the local recognition task. The Two-Dimensional Discrete-State model is a slot model augmented with the assumption that some of the features of an object in a slot might be omitted (Cowan, Blume, & Saults, 2013), so that item information and location information can be lost independently.

On an abstract level one can think of a unidimensional model is a special case of a Two-Dimensional model, or a Discrete-State model as a special case of a Continuous-Strength model. It turns out, however, that formalizing the four model classes in this way unduly disadvantages the special cases. To give unidimensional models, and Discrete-State models, a fair chance of accounting for the data from local-recognition experiments, they require specific assumptions that implement alternative explanations – not just simpler ones – to those incorporated in Two-Dimensional Continuous-Strength models. Therefore, the models considered in this study are not nested in each other. We developed each model based on proposals in the literature for how to make that kind of model work, so that they all had a good chance of capturing the results from the local recognition task. Some assumptions are shared between models, but because of the other assumptions incorporated in the models, none of the models are nested.

Unidimensional Discrete-State model

In the Unidimensional Discrete-State model, we assumed that an object (i.e., a conjunction of a context with a content) is stored in working memory, as long as free slots are available – which happens with probability Pm. The object representation usually contains the correct context and content binding. However, there is a chance that a swap error occurs at encoding. Given that two objects i and j are encoded into memory, the probability of swapping them, $Ps(i,j)$, depends on the distance between their serial positions:

$$Ps(i,j) = b \cdot \exp(-s \cdot |i - j|). \quad (1)$$

A swap error is more likely to occur between neighboring objects than between objects far apart in the list. This assumption incorporates the "locality constraint" on swap errors observed in serial-order memory of verbal and spatial materials (Hurlstone, Hitch, & Baddeley, 2014). The probability of an object retaining the correct binding is $1 - \sum_{j \neq i} Ps(i,j) \cdot Pm(j)$, which is the probability that the object is encoded, and swap errors did not occur between object i and any of the other objects. The possible memory states of the Unidimensional Discrete-State model are illustrated in Figure 2.

The recognition process of the Unidimensional Discrete-State model is illustrated in Figure 3. The probe object is compared to all the remembered objects. The probe is accepted if the probe object matches one of the remembered object. The probe is accepted if either the context of the probe or the content was remembered together with another context or content. If none of the probe context or the probe content was remembered in the memory, a guess response is given. Therefore, the probability of accepting the probe, $P_{yes}(i,i)$ for content i presented at context i is:

$$P_{yes}(i,i) = Pm(i) \cdot \left[1 - \sum_{j \neq i} Ps(i,j) \cdot Pm(j)\right] + [1 - Pm(i)] \cdot g \tag{2}$$

$Pm(i)$ is the probability of the target object being in memory, and $\left[1 - \sum_{j \neq i} Ps(i,j) \cdot Pm(j)\right]$ is the probability of the target object retaining the correct context-content binding. If the target object is not remembered – with probability $1 - Pm(i)$ – then the observer guesses and accepts the probe with probability g.

For a new probe presented at context i, the content x of the new probe has not appeared in the memory set. Therefore, regardless of whether a swap error occurred for target object i or not, the content of the probe does not match the content at context i. As long as object i is memorized, the new probe is rejected. If no information about object i is in memory, the model has to guess. Thus, the probability of accepting the new probe is

$$P_{yes}(x,i) = [1 - Pm(i)] \cdot g. \tag{3}$$

There are two possibilities to falsely accept an intrusion probe that consists of the content i presented in context j. First, if both object i and object j are not represented in memory – with probability $[1 - Pm(i)] \cdot [1 - Pm(j)]$ – the observer has to guess, and then the intrusion probe is accepted through guessing with probability g. Second, if both object i and object j are held in memory, and a swap error has occurred between objects i and j, the intrusion probe is falsely accepted. Note that any other swap error between object i and the objects other than j, e.g., swap error between i and $k,$ would lead to rejecting the intrusion probe because k mismatches j. Taken together, the probability of responding *yes* to an intrusion probe is:

$$P_{yes}(i,j) = Pm(i)Pm(j)Ps(i,j) + [1 - Pm(i)] \cdot [1 - Pm(j)] \cdot g. \quad (4)$$

The Unidimensional Discrete-State model is a unidimensional model because if an item is remembered, it is always remembered in conjunction with a context (even if the wrong context). During recognition, only one source of information is used: The conjunction of the context and the content of the target object in memory. The availability of that information varies along a single dimension, with only two values that are treated differently by the decision process: The target object is or is not in memory. The model is a Discrete-State model because an object is either remembered or not remembered, and the recognition process results in one of three discrete states: the detection of a match, the detection of a mismatch, or a guessing state.

Two-Dimensional Discrete-State Model

The Two-Dimensional Discrete-State model incorporates the assumption of Cowan et al. (2013) that some of the features of an object stored in a slot might be omitted, and the recognition decision varies depending on the number of matching features. We assume that in the present local recognition task an object consists of two features: content feature and context feature. The content feature is the content of the object, and the context feature is its location. A memory of an object could contain only the content feature, only the context feature, or both features.[2] Because in our version of local recognition, the same set of locations is used on every trial, having only the location feature in memory does not provide useful information for the recognition decision. Even a new probe is always presented in one of the old locations. Therefore, we treat the situation when only the context feature of the probe is stored in a memory slot like the situation in which no feature of the probe is stored: In both cases, the observer can only guess. The possible memory states of the Two-Dimensional Discrete-State model after encoding are illustrated in Figure 4.

When the probe item i matches a content feature form i in a memory slot, the observer tries to access the context feature in that slot. If the slot contains a context feature, the probe is either accepted (i.e., the probe context matches the context in the slot) or rejected (i.e., the probe context mismatches the context in the slot) without leaving room of guessing. If the slot contains only the content feature i without any context feature, uncertainty arises. Because a context feature is lacking, the content feature alone only provides the information that the probe matches an item in the memory set, but not whether the item has been presented in the probe's location or not. This information is sufficient to rule out a new probe, but not to distinguish between positive and intrusion probes. We assume that being in this state of partial information leads to a partial-information guessing; hence g_{plus} denotes to the probability of *yes* response when the probe's content feature matches a content of an stored object that is not accompanied by any context feature. The recognition process of Two-Dimensional Discrete-State model is illustrated in Figure 5.

The probability of responding *yes* to a positive probe is formalized as:

$$P_{yes}(i,i) = Pm(i)Pb(i) + Pm(i)[1 - Pb(i)] \cdot g_{plus} + [1 - Pm(i)] \cdot g, \tag{5}$$

where $Pm(i)$ denotes the probability of having object i in the memory, regardless of whether this representation contains only the content feature or both content and context features, and $Pb(i)$ is the probability of that object having its context feature bound to it. If both content and context feature are included in object i – with probability $Pm(i)Pb(i)$ –, the model enters an informed decision process and correctly accepts the positive probe. In the case of having the content feature but without context feature ($Pm(i)[1 - Pb(i)]$), the model guesses with a certain level of confidence (g_{plus}). In the case of not having object i in memory, the model has to guess without any information (g).

In the Two-Dimensional Discrete-State model, the new probe can only be accepted through random guessing when the probed context is not stored together with its item (i.e., the probed context is either stored alone without any content, or not at all). Thus, the probability of accepting the new probe is:

$$P_{yes}(x, i) = [1 - Pm(i)Pb(i)] \cdot g. \tag{6}$$

The intrusion probe, content i presented at context j, can be accepted through two routes. The first route is accepting the intrusion probe by only having the content feature of object i in memory without context features. The content feature of the probe matches one of the contents in the memory. However because of the lack of a context feature, the intrusion probe is accepted with partial-information guessing probability g_{plus}. This route requires that the object i is in memory but without its context feature, which happens with probability $Pm(i)[1 - Pb(i)]$, and at the same time, the context j is not in memory together with content j, which occurs with probability $1 - Pm(j)Pb(j)$. If the content and context features of object j are both in memory, the intrusion probe will be successfully rejected through content mismatch, because the content j should be presented at context j instead of content i. Hence, the probability of accepting the intrusion probe through partial-information guess is:

$$Pm(i)[1 - Pb(i)] \cdot [1 - Pm(j)Pb(j)] \cdot g_{plus}.$$

The second route to accepting an intrusion probe is to accept it through random guessing with probability g in the absence of any information. In order to not have any information about the intrusion probe, the content feature i of the probe must not be in memory at all (occurring with probability $1 - Pm(i)$, and its context feature j must not be in memory together with the correct content (with probability $1 - Pm(j)Pb(j)$). Taken together, the probability of accepting an intrusion probe is:

$$P_{yes}(i,j) = Pm(i)[1 - Pb(i)] \cdot [1 - Pm(j)Pb(j)] \cdot g_{plus} + [1 - Pm(i)] \cdot [1 - Pm(j)Pb(j)] \cdot g. \tag{7}$$

The Two-Dimensional Discrete-State model is a Two-Dimensional model because the memory trace accessed for recognition can either contain both content and context feature in conjunction (i.e., having binding information), or contain only the content feature (i.e., having only item information). Thus, the availability of memory information varies along two dimensions – availability of content memory, and availability of content-context bindings, and the distinctions on both dimensions make a difference for the decision process. The model is a Discrete-State model because the memory trace of the content-context binding, or of the context-less content, is either present or absent, and the recognition process results in either detecting a match or detecting a mis-match between the probe and a memory representation, or detecting the absence of any relevant information (i.e., entering a guessing state).

Unidimensional Continuous-Strength model

The Unidimensional Continuous-Strength model is the same as the single-process model in Oberauer (2008), which builds on the model by Brockdorff and Lamberts (2000). In this model, all items are encoded into working memory with a continuously varying strength. The Unidimensional Continuous-Strength model is a summed-similarity model: The similarities between each object and the probe, weighted with the object's strength, are summed into a single signal used for recognition. The similarity takes both content and context into account. The possible memory states of the Unidimensional Continuous-Strength model after encoding is illustrated in Figure 6.

The similarity between each memory object i and probe j, $s_{i,j}$, is calculated through

$$s_{i,j} = \exp\{-c_s \cdot [u \cdot D_{content}(i,j) + (1-u) \cdot D_{context}(i,j)]\}. \tag{8}$$

$D_{content}(i,j)$ and $D_{context}(i,j)$ are dummy codes for content and context mismatch between object i and probe j, which are set to 0 if it is a match or 1 if it is a mismatch. Parameter u is the relative weight of content match and context match; u ranges from 0 to 1. The combined match is then scaled with parameter c_s, which ranges from 0 to infinity and determines the minimum similarity when both content and context mismatch. When both content and context match, the similarity becomes $\exp(0) = 1$, which is the maximum similarity. When both content and context mismatch, the similarity between object i and probe j is $\exp(-c_s)$, which decreases when c_s increases.

The memory signal for accepting a probe is the summed similarity between probe and each object, weighted by the memory strength w_i of each object, which is formulated as:

$$e = \sum_{i=1}^{n} w_i \cdot s_{i,probe}. \tag{9}$$

The signal is different among the types of probes. Regardless of the type of probes, the context of the probe always matches one of the items, because in our local recognition task, the probe always appears in the location of a memory item. The intrusion probe and the positive probe have a content match in addition to the constant context match, hence intrusion probes and positive probes receive stronger memory signals than new probes. Though positive probe and intrusion probe both have one content and one context match, a positive probe has content and context matches on the same item, whereas an intrusion probe has content and context matches on different items. Because of the nature of the exponential, the combined similarity of one context-matching object and another content-matching object ($\exp(-c_s u) + \exp[-c_s(1-u)]$) is guaranteed to be smaller than (when $c_s > 0$) or equal to (when $c_s = 0$) the combined similarity of a completely mismatching object and a completely matching object ($\exp(-c_s) + 1$). Therefore, a positive probe generates a stronger memory signal than an intrusion probe. However, because an intrusion probe generates a stronger signal than a new probe, an intrusion probe has a higher chance to be accepted than a new probe.

To convert the memory signal into the probability of accepting the probe, we used the logistic function on the signal via

$$P(yes) = \frac{1}{1 + \exp[-\lambda \cdot (e - \tau)]}, \quad (10)$$

where λ and τ are free parameters for slope and midpoint of the logistic function, respectively. The logistic function becomes steeper when λ is larger, so that the model is more sensitive to small differences in signal strength. The midpoint τ can be interpreted as the criterion of accepting or rejecting the probe. When the signal of a probe exceeds τ, the probe is more likely to be accepted than to be rejected. We chose the logistic function because it can be interpreted as the probability that a noisy signal e exceeds a threshold τ, with λ reflecting the degree of noise.

The Unidimensional Continuous-Strength model is a unidimensional model because the recognition process relies on a single global-similarity signal that reflects the overall match of the probe to memory representations with regard to both content and context. The strength of that signal varies along a single dimension. The memory objects are remembered with continuously varying strength. The continuous strength modulates the amount each object contributes to the recognition signal, which results in a continuously varying recognition signal, therefore the model is a continuous model.

Two-Dimensional Continuous-Strength model

The Two-Dimensional Continuous-Strength model is adapted from the dual-process model in Oberauer (2008). The model assumes there are two sources of signals: familiarity and recollection. The difference between familiarity and recollection is the scope of comparison. The familiarity compares the probe to all the items in the memory set regardless of their context, whereas the recollection compares the content-context conjunction of the probe to the content-context bindings in memory. The familiarity process returns the summed similarity of the probe content to all items in memory regardless of the context of the probe. The recollection process, in contrast, assesses whether the probe matches the context and content of an object at the same time, such that a match only in content, or only in context, counts as a mismatch. The possible memory states of the Two-Dimensional Continuous-Strength model after encoding are illustrated in Figure 7.

In the Two-Dimensional Continuous-Strength model, the signal of familiarity arises from the match of the probe to one of the contents in the memory set. The signal from familiarity, e_{fam}, is either 1 when the content of probe matches a content in the memory set regardless of the location of the probe or 0 when the item of the probe does not match any items in the memory set.

The signal of recollection comes from two different retrieval directions: Recollection 1 retrieves the content at the probed context (i.e., the location), and Recollection 2 retrieves the context from the content of the probe. Assuming the probe is $p_{j,i}$, in which item j is presented at location i, Recollection 1 returns the match between the content of the probe and the content encoded at the probed context, $M(probe_{content}, i)$, which is 1 in case of a match and -1 in case of a mismatch. The negative match value reflects the assumption that a mismatch provides a signal against accepting the probe. The signal from Recollection 1, $e_{content}$, is determined by the match $M(probe_{content}, i)$, modulated by the memory strength of the retrieved content, which is:

$$e_{content} = w_i \cdot M(probe_{content}, i). \tag{11}$$

Recollection 2 uses the probe content to retrieve the context bound to it, and assesses the match between the retrieved context and the context of the probe, $M(probe_{context}, j)$. If the retrieved context matches the context of the probe, $M(probe_{context}, j)$ is set to 1. If the retrieved context does not match the context of the probe, $M(probe_{context}, j)$ is set to -1. If the location cannot be retrieved in case of a new probe, $M(probe_{context}, j)$ is set to 0.[3]. The signal from Recollection 2, $e_{context}$, is weighted by the memory strength of the retrieved location, w_j. In case of failure to retrieve the location, $w_j = 0$. Thus, the Recollection 2 signal is:

$$e_{context} = w_j \cdot M(probe_{contenxt}, j). \tag{12}$$

The overall signal from recollection is the weighted average between content match and context match:

$$e_{rec} = d \cdot e_{content} + (1 - d) \cdot e_{context}. \tag{13}$$

The parameter d is the relative weighting of content match and ranges between 0 and 1. When the parameter d is 1, the recollection signal is solely determined by content match. When d is 0, only context match is taken into account.

The signal from familiarity and the signal from recollection are then combined via:

$$e \ = m \cdot e_{fam} + (1 - m) \cdot e_{rec}, \tag{14}$$

where the parameter m is the relative weighting of familiarity. The combined signal, e, is then used to determine the probability of accepting the probe with a logistic function in Equation 9, as in the Unidimensional Continuous-Strength Model. In this model, a positive probe receives a positive familiarity signal, because its content matches one of the memory items, and a positive recollection signal, because both directions of retrieval return a match. A new probe receives a low familiarity signal, and a negative recollection signal (through Recollection 1), making it easy to reject. An intrusion probe receives a positive familiarity signal but a negative recollection signal (from both directions of retrieval); the conflict of the two signal dimensions makes intrusion probes hard to reject.

In the Two-Dimensional Continuous-Strength model, the recognition signal comes from two separate sources: familiarity and recollection, and both sources rely on different types of information in the memory, which makes the model a Two-Dimensional model. The memory objects are remembered with continuous strength, similar to the Unidimensional Continuous-Strength model, and this strength modulates the contribution from an object to the recognition signal. Therefore, the model is a continuous model.

Predictions for serial-position effects

In this study, we wanted to ensure that we gave every model its best chance to simulate the serial-position effect, thus we gave the models a high degree of flexibility without violating the core assumptions of the models. Because of the different core assumptions of Discrete-State and Continuous-Strength models, we had to make different assumptions about the mechanisms generating serial-position effects in these models. For Discrete-State models, because objects are either remembered in a slot or forgotten entirely, we assumed that the *probability* of remembering the objects varies across serial positions. For Continuous-Strength models, we assumed that all objects are encoded into memory with variable strength, and the *strength* of objects varies across serial positions. Because the purpose of this research is not to explain the serial-position effect, but to use it for testing between the four models outlined above, we simply describe the serial-position effect as a combination of primacy and recency effects. In the Discrete-State models, the probability of remembering the object at the serial position i is:

$$Pm(i) = \max[1, \frac{d_m \cdot m_p^{i-1} + m_r^{n-i}}{\sum_l^n d_m \cdot m_p^{l-1} + m_r^{n-l}} \cdot k] \quad (15)$$

where n is the set-size of the trial. The parameters m_p and m_r range from 0 to 1 and represent primacy and recency effects, respectively, and the parameter d_m is the strength of the primacy effect relative to that of the recency effect. The primacy and recency effects are more pronounced when their respective parameters are closer to zero, and the relative strength of primacy effect over recency effect is stronger if parameter d_m is larger. The parameter k is the number of objects that can be held in memory. The probability of encoding the context feature ($Pb(i)$) in the Two-Dimensional Discrete-State model is also assumed to vary across the serial positions. The serial-position effects of $Pb(i)$ are

$$Pb(i) = \max\left(1, d_b \cdot b_p^{i-1} + b_r^{n-i}\right) \tag{16}$$

where the b_p represents the primacy effect, and the b_r represents the recency effect, and d_b represents the relative strength of primacy effect compared to recency effect.

For the continuous models, the strength across the serial position is described in a similar way:

$$w_i = d_w \cdot w_p^{i-1} + w_r^{n-i}. \tag{17}$$

The constraints on w_p and w_r are the same as in the Discrete-State models. We then normalized the memory strength with $\sum_i^n w_i = 1$. This ensures that the sum of memory strength is constant across set sizes.[4] In the Unidimensional Continuous-Strength model, Eq. (16) describes the strength of the content-context conjunctions representing each item. In the Two-Dimensional Continuous-Strength model, Eq. (16) describes the strength of bindings that affects the recollection signal. As in Oberauer (2008), we assume that familiarity is not affected by serial position, because there is nothing in the available data that would require the additional flexibility of allowing familiarity to vary across serial positions.

Predictions for effects of the probed position

As in Oberauer (2008), we initially focus on the effect of the serial position of the probed location on accuracy. By serial position, we meant the ordinal position of presentation of the list items, which in our experiments corresponds to the left-right position of each item's location. The serial-position effects can be assessed for each probe type because the serial position is defined by the position of the probed location. We ignored the serial-position effects on reaction time because the Discrete-State models are not well suited for predicting serial-position effects on reaction time.

Both Two-Dimensional models and the Unidimensional Discrete-State model predict serial-position curves that are U-shaped for all three types of probes, such that the probes tested at the beginning and the end of list have better performance compared to the probes tested at the middle of the list. In contrast, the Unidimensional Continuous-Strength model predicts inverted U-shaped serial-position curves for intrusion and new probes, as shown in Figure 8.

Predictions of effects of the position of origin of intrusion probes

The accuracy of rejecting intrusion probes can also be investigated as a function of the position of origin of the probe content. As shown in Figure 9, all models except for the Unidimensional Continuous-Strength model are able to generate a U-shape for accuracy over position of origin, whereas the Unidimensional Continuous-Strength model must predict an inverted U-shaped curve over position of origin. However, the Two-Dimensional Discrete-State model is able to generate both U-shape and inverted U-shape position-of-origin effects for intrusion probes, depending on the parameters. Despite the constraint of only generating U-shaped serial-position effects on $Pm(i)$ and $Pb(i)$, the Discrete-State models are able to predict both U-shaped and inverted-U shaped position-of-origin effects, because $Pm(i)$ and $Pb(i)$ are allowed to produce independent serial-position curves. If the extra flexibility in this model is constrained, for instance by assuming that $Pb(i)$ is constant across serial positions, Two-Dimensional Discrete-State model can only predict an inverted-U-shaped position-of-origin effect. However, it is reasonable to assume that the probability of remembering the context feature varies across serial positions. Therefore, we kept the Two-Dimensional Discrete-State model with extra flexibility in predicting the position-of-origin effect.

Because the position-of-origin effect is not diagnostic for the Two-Dimensional Discrete-State model, we only used the position-of-origin effect to distinguish between the remaining three models. The Two-Dimensional Discrete-State model and the models which can correctly predict the position-of-origin effect were then compared based on the goodness-of-fit from the model fitting.

Experiment 1

To test the serial-position effects for which our models make predictions, we carried out three local-recognition experiments with visual stimuli. The experimental procedure was similar across all three experiments. What differed between the experiments is the stimulus material. Experiment 1 used Chinese characters, and Experiments 2 and 3 used color patches.

Method

Participants

Ten students were recruited from the University of Zurich. None of the participants was a Chinese speaker. Participants had normal or corrected-to-normal vision. Participants were rewarded with course credits or 60 Swiss Francs after completing the experiment. Two participants were excluded from the analysis because they failed to complete the experiment.

Materials

109 Chinese characters consisting of between 4 and 6 strokes were used in the experiment. The characters were selected to avoid extremely high confusability (e.g.: avoiding 今 and 令).

Procedure

The experiment consisted of four sessions on different days. Each session included 400 experiment trials and 10 practice trials and took about one hour to complete. The procedure of each trial is shown in Figure 1. At the beginning of each trial, five empty frames were displayed horizontally with even space between each frame. After 500 ms, five characters were displayed sequentially in the frames in a left to right order, with 800 ms display time for each character. After the offset of the last character and a 500 ms retention interval, a probe was displayed in one of the frames. Participants were instructed to recognize if the probe was the same as the item displayed earlier in the same frame by pressing the *left* or *right* arrow key for “different” or “same” response, respectively. There were three types of probes: positive, new, and intrusion probes. A *positive probe* was the same as the item displayed in the probed frame. Participants should respond "same" for positive probe. A *new probe* was an item which did not appear in the memory set. Participants should respond "different" for new probes. An *intrusion probe* was an item that appeared in the memory set but in another frame than the probe. Participants should respond "different" for intrusion probes. After responding to the probe, a blank screen was shown for 1000 ms, followed by the beginning of the next trial.

In each session, there were 200 trials of positive probes, 100 trials of new probes, and 100 trials of intrusion probes, and the order of probe types was randomized. All the serial positions were tested with equal probability. In case of the intrusion probes, each combination of position of origin and serial position of probe occurred with equal frequency.

The experiment was exempted from reviewing by the ethics committee of University of Zurich according to the initial checklist provided by the ethics committee.

Results

The trials with reaction times longer than 5 seconds were discarded from the analysis as outliers, which resulted in 285 (1.87%) trials excluded in Experiment 1. The remaining trials were analyzed with the BayesFactor package (Morey & Rouder, 2015) in R (R. Core Team, 2016). For accuracy, there was strong evidence supporting the effect of probe type ($BF_{10} = 388.45$) and serial position ($BF_{10} = 1.55 * 10^8$) in comparison to the null model. The interactive effect between probe type and serial position was strongly preferred ($BF_{10} = 172.22$) over the model including only the main.

Because the serial-position effect is important to differentiate the models, we also tested evidence for the quadratic trend across the serial positions, which reflects whether we obtained U or inverted-U shape serial-position effect. We analyzed the serial-position effect for the three types of probes separately and compared the quadratic trend along with linear trend model to the linear trend model. The quadratic trend model was strongly supported in all three types of probes against the linear trend model (Positive probe: $BF_{10} = 30$; New probe: $BF_{10} = 47659$; Intrusion probe: $BF_{10} = 2.28e + 8$). We also tested the quadratic trend for intrusion probes across the position of origin, in comparison to the linear trend. The evidence strongly supported the quadratic trend ($BF_{10} = 191.05$). The summary of statistical results is given in Table 2.

Experiment 2

In Experiment 2, we changed the material from Chinese characters to color patches in order to test the four models with simple visual stimuli as they are most commonly used in change-detection experiments.

Method

Participants

Twenty students were recruited from the University of Zurich. Participants had normal or corrected-to-normal vision and were not color blind. Participants were rewarded by course credits or 45 Swiss Francs once they completed the experiment. One participant was excluded from the analysis because of failure to complete the experiment.

Materials

The stimuli in Experiment 2 were color patches randomly selected from a color wheel which was created in the CIE L*a*b* color model with a radius of 60 and centered at luminance set to 70, *a* set to 20, and *b* set to 38. Additionally, the minimum similarity between any two colors used in the same trial was constrained to be larger than 30° in the color wheel.

Procedure

Experiment 2 consisted of three sessions on different days. Each session consisted of 10 practice trials and 320 experiment trials, and took about one hour to finish. The experiment trials were reduced to 320 trials from 400 trials in Experiment 1 to ensure that participants can finish a session in an hour. In the 320 experiment trials, 160 trials were probed with positive probes, 80 trials were probed with new probes, and the remaining 80 trials were probed with intrusion probes. The procedure of each trial in Experiment 2 was the same as in Experiment 1.

The experiment was exempted from reviewing by the ethics committee of University of Zurich according to the initial checklist provided by the ethics committee.

Results

As in Experiment 1, the trials with reaction time longer than 5 seconds were excluded as outliers, which removed 274 (1.63%) trials. The remaining trials were analyzed with the

BayesFactor package in R. The accuracy results show strong evidence supporting the effect of probe type and serial position ($BF_{10} = 1.76e + 26$ and $BF_{10} = 1414.80$, respectively) when comparing the main effect model to the null model. The interaction between probe type and serial position was also supported with strong evidence ($BF_{10} = 2.8e + 8$) when comparing the full model to the model which only contains the two main effects. The quadratic trend across serial positions for accuracy was supported for positive probes and intrusion probes comparing to the linear trend model (Positive probe: $BF_{10} = 19202$; Intrusion probe: $BF_{10} = 4.74$), but the evidence was against the quadratic trend for new probes ($BF_{10} = 0.33$). The evidence strongly supported the quadratic trend over position of origin for the intrusion probes ($BF_{10} = 23.28$). A summary of the statistics is shown in Table 2.

Experiment 3

In Experiment 2, the performance on the positive probes was much lower than in Experiment 1. At the same time, the performance on new and intrusion probes was slightly higher. This could indicate that participants had a bias towards rejecting the probe. We suspected that this is the result of similar color patches being used repeatedly. As a consequence, new probes often matched a color used in a recent previous trial, which makes them difficult to reject (McElree & Dosher, 1989). As a consequence, participants apparently have adopted a bias towards rejecting probes. In Experiment 3 we ensured that new probes did not match the items from recent trials in the hope to reduce that bias.

Participants

Twenty students were recruited from the University of Zurich. Participants had normal or corrected-to-normal vision and were not color blind. Participants also did not take part in

Experiment 2. Participants were rewarded with course credits or 45 Swiss Francs once they completed the experiment.

Materials

Twelve colors from the color wheel were randomly selected for each session, such that all colors were 30 degrees apart from their next neighbors in the color wheel. The same twelve colors were used repeatedly across the whole sessions. However, when selecting the colors for new probes, we ensured that the color was not presented in any of the five most recent trials. At each trial, one color was taken away from the pool and would not be as an object color nor a probe color for the next five trials. At the sixth trial, if the probe was a new probe, the preserved color was selected as the color of probe. Regardless if the color was used in the sixth trial, the color was put back to the pool after the sixth trial.

Procedure

Participants went through the same procedure as in Experiment 2. The experiment was exempted from reviewing by the ethics committee of University of Zurich according to the initial checklist provided by the ethics committee.

Result

To remove outliers, the trials with reaction times longer than 5 seconds were excluded from analysis, which removed 257 (1.34%) trials. The remaining trials were analyzed with the BayesFactor package in R. The accuracy data provided strong evidence in support of the effect of probe type and the effect of serial position (BF = 1.6e+5 and BF = 351.62, respectively). The interaction between probe type and serial position was also supported with medium evidence (BF = 7.95). The quadratic trend across serial position effect for accuracy was supported for positive probes (Positive probe: $BF_{10} = 59.26$), but the evidence was ambiguous regarding the quadratic trend for new probes ($BF_{10} = 0.49$) and intrusion probes ($BF_{10} = 0.42$). The evidence supported the quadratic trend for the intrusion probes as a function of position of origin ($BF_{10} = 3.35$). The summary of statistical results is given in Table 2.

Model Comparison

Throughout the three experiments in the study, the quadratic trend of serial-position effect was shown for all the positive probes. However, only Experiment 1 showed a quadratic trend of serial-position effect on new probes, and the quadratic trend of serial-position effect on intrusion probe was only supported in Experiments 1 and 2. Although the quadratic trend was not always supported, when it was, it consistently showed a U-shaped serial-position effect, which follows the prediction of the Two-Dimensional Continuous-Strength model and Discrete-State models. The Unidimensional Continuous-Strength model predicts an inverted U-shape serial-position effect for new probes and intrusion probes, which is inconsistent with the results. In addition, all the experiments showed a U-shaped serial-position effect on accuracy of intrusion probes across their position of origin. All the models except the Unidimensional Continuous-Strength model are capable of predicting this pattern, whereas the Unidimensional Continuous-Strength model predicts an inverted U-shape for performance across position of origin.

Taken together, the Unidimensional Continuous-Strength model failed to predict most of the serial-position effects from the local recognition task. Because the Unidimensional Continuous-Strength model computes signal strength as the summed similarity between the probe and memory objects, weighted by each object's memory strength, the Unidimensional Continuous-Strength model cannot predict the same shape of the serial-position effect for positive, new, and intrusion probes.

. To correctly predict the U-shape of the serial-position curves for new and intrusion probe, the encoding strength at the beginning and the end of the list needs to be lower than the encoding strength for the objects in the middle of the list, so that less summed similarity originates from the beginning and the end of the list. This would imply that the positive probes receive less summed similarity from matching items at the beginning and the end of the list than from items in the middle, which results in an inverted U-shape of the serial-position curve for positive probes. Therefore, the Unidimensional Continuous-Strength model cannot predict the present results.

Model Fitting

Unlike the Unidimensional Continuous-Strength model, the other three models are able to generate the shapes of the observed serial-position curves. To further compare the models, we fitted these three models to the results of the three experiments separately. The models were implemented in Python 3.5, and their parameters optimized with the differential evolution algorithm (Storn & Price, 1997) in SciPy (Jones, Oliphant, Peterson, & others, 2001) with the maximum likelihood method. In order to minimize the risk of running into a local minimum, the model fitting was repeated 10 times for each participant, using different starting populations of parameter values in differential evolution, and the best fitting solution was kept. Model fit was assessed with the AIC, which derives from $-2 * log(Likelihood)$ by adding a penalty term of $2 * n$ where the n is the number of free parameters; lower AIC values indicate a better fit. The results are listed in Table 3, the estimated parameters are listed in Table 4, and the model prediction are shown in Figures 11, 12, and 13. The AIC shows that the Two-Dimensional Continuous-Strength model performed best in all three experiments by a substantial margin. Even when evaluated on the $log(Likelihood)$, which does not take the number of free parameters into account, the Two-Dimensional Continuous-Strength model outperformed the Discrete-State models in all the experiments. The misfit of the Discrete-State models comes primarily because these models have difficulty producing intrusion costs (i.e., the difference in accuracy between new and intrusion probes).

To illustrate the issue, in Figure 14 we plotted the intrusion costs predicted by the Discrete-State models and the Two-Dimensional Continuous-Strength model with their best-fitting parameter values, against the intrusion costs observed in the three experiments. Both Discrete-State models predicted intrusion benefits instead of intrusion costs, which generates significant misfit for the model. The Two-Dimensional Continuous-Strength model, in contrast, predicts the intrusion costs in close agreement with the empirical data.

The Unidimensional Discrete-State model predicts an intrusion benefit instead of an intrusion cost when using its best-fitting parameter values. This is because in the Unidimensional Discrete-State model, the intrusion probe, content i presented at context j, can be rejected by accessing the memory representation from both directions, either by remembering the correct content-context binding at the probed location – with probability $Pm(i)[1 - Ps(i,j)]$ – or by remembering the correct binding at the position of origin – with probability $Pm(j)[1 - Ps(i,j)]$. However, the new probe can only be successfully rejected by remembering the target object memory at the probed location – with probability $Pm(i)$. Therefore, the Unidimensional Discrete-State model can predict an intrusion cost only with high values of $Ps(i,j)$. Such high swap probabilities, however, force the model to predict lower accuracy on positive probes than was observed.

The Two-Dimensional Discrete-State model predicts an intrusion benefit with its best-fitting parameters for a similar reason. In the Two-Dimensional Discrete-State model, the new probe, content x presented at context i, can be correctly rejected by having in memory the item i

together with its context feature – with probability $Pm(i)Pb(i)$ – because the content of the probe (x) does not match the content stored together with the probed location (i). However, an intrusion probe, content j presented at context i, can be correctly rejected by accessing memory representations from two directions, either by remembering the content and context feature at the probed context – with probability $Pm(i)Pb(i)$ – or by remembering the probed content j with its corresponding context j – with $Pm(j)Pb(j)$. Because the intrusion probe can be rejected by having in memory the context feature at either the probed location or at the probe's position of origin, it has a higher chance of being rejected on the basis of a mismatching memory representation than a new probe. Therefore, unless the guessing with partial-information (g_{plus}) is very high, the Two-Dimensional Discrete-State model predicts an intrusion benefit instead of an intrusion cost. Even if g_{plus} is high enough, the model still does not predict a large enough intrusion cost, resulting in a poor model fit.

Discussion

In this study, we compared four models generated by fully crossing two theoretical distinctions. Our results show that the Two-Dimensional Continuous-Strength model performed the best compared to the other models. All the models except the Unidimensional Continuous-Strength model can qualitatively predicted the shapes of the serial position curves. However, the Two-Dimensional Continuous-Strength model provided the best quantitative model fit, because it is the only model that can produce a sufficiently large intrusion cost.

Alternative Model Variants

The Two-Dimensional Discrete-State model failed to predict the intrusion cost because the intrusion probe can be rejected through having the correct binding of the probed content, or having the correct binding of the probed context. Both sources of rejecting the intrusion probe are important. The access of content from the context location, similar to Recollection 1 in the Two-Dimensional Continuous-Strength model, is important for generating the serial-position curve of the new probe. Because context is the only matching feature of the new probe, retrieval can only use the matching context to access the corresponding content. If that retrieval route in the Two-Dimensional Discrete-State model is removed, the new probe can only be rejected with guessing probability g, which is constant across serial positions. The converse retrieval route, accessing of context corresponding to the probe's content (akin to Recollection 2) is also an important process in the Two-Dimensional Discrete-State model. The model assumes that an object can be remembered but only contains the content feature without the context feature. Using the content feature matching the probe to access the context bound to it, and failing, leads to partially informed guessing. This mechanism implies that the model uses the probe's content to find an object with matching content in memory, and access its context. It is reasonable to assume that this retrieval route is also used when the context features are remembered together. To conclude, both context retrieval and content retrieval process are required in the Two-Dimensional Discrete-State model. Together they imply two routes to rejecting an intrusion probe based on information from memory, but only one route to reject a new probe. Therefore, the model has difficulties predicting an intrusion cost.

The Set-size Effect on Intrusion Costs

Donkin et al. (2015) introduced the Unidimensional Discrete-State model with swap errors to account for intrusion costs. They investigated the effect of memory set size on the size of the intrusion cost, and found that the intrusion cost increased between set-size 2 and set-size 4, then remained fairly constant between set-size 4 and set-size 8. They applied a Unidimensional Discrete-State model very similar to the one we used to their data, and found that it predicted a reduction of the intrusion cost as set size increases. Therefore, Donkin et al. interpreted the set-size effect on intrusion costs as a challenge for Discrete-State models of visual working memory.

We found that, although the Discrete-State models failed to predict the absolute size of the intrusion cost, the Two-Dimensional Discrete-State model is able to predict the set-size effect on the intrusion cost. In Two-Dimensional Discrete-State model, the probability of having the correct the context feature varies across serial positions. According to Equation 15, Pb is relatively constant at the beginning of the list across different set sizes, where the effect of the recency gradient is minimal (r_b^{n-i}), and analogously, Pb is relatively constant at the end of the list, where the effect of the primacy gradient is minimal. The Pb in the middle of the list is much lower than the Pb at the beginning and the end of the list, and increasing the set size increases the number of elements in the middle of the list, which results in reducing the average Pb when set size increases. Figure 15 (left) is the prediction of the set-size effect of Two-Dimensional Discrete-State model. Although the model still does not predict a sufficiently large intrusion cost in smaller set sizes, the model predicts the increase of the intrusion cost between set-size 2 and set-size 4, and its constant size between set-size 4 and set-size 8.

The Two-Dimensional Continuous-Strength model can also predict a set-size effect for the intrusion cost. In Figure 15 (right panel), the intrusion cost increases throughout the set sizes. This happens because the sum of the memory strength is constant, therefore the larger set sizes leads to smaller memory strength for individual items. Because the intrusion probe is rejected through the recollection process, and the strength of the rejection is tied to the memory strength, the reduction of the memory strength results in increasing the intrusion cost.

The assumption of a constant total memory strength effectively implements a resource model of working memory (Ma, Husain, & Bays, 2014). Resource models are one way of fleshing out the class of Continuous-Strength models, and we use it here to illustrate how the Two-Dimensional Continuous-Strength model can predict the increase of intrusion costs with set size. The Two-Dimensional Continuous-Strength model, however, is not tied to the assumption of a limited resource; it can also be combined with other assumptions about why memory performance decreases with increasing set size. For instance, we recently proposed an interference model of visual working memory (Oberauer & Lin, 2017) in which memory strength varies continuously. Moreover, the interference model assumes two sources of memory strength, the activation of individual items regardless of their context, and the activation of items recreated at retrieval through their bindings to a context that serves as retrieval cue. Therefore, the architecture of the interference model fits the core assumptions of the Two-Dimensional Continuous-Strength model. So far we have not applied the interference model to local recognition/change detection tasks. The present results are encouraging for such an attempt.

The effect of variable set sizes on discrete/continuous model

Donkin et al (2014) found that participants show more Discrete-State model like behavior when the set sizes varied in the same experimental session, and participants shown more Continuous-Strength model like behavior when set sizes are fixed in the same session. Donkin et al argued that this could be so because participants utilized different strategies at allocating their attention. The set size was fixed in all our experiments, and indeed we found the evidence supports a Continuous-Strength model over Discrete-State models. The support for Continuous-Strength model is possibly due to participants' strategy. However, in our study, the misfit from Discrete-State models comes from underestimating the size of the intrusion cost, and intrusion probes were not included in Donkin et al (2014)'s study. In Donkin et al (2015)'s study, in which the authors manipulated the set sizes within session and included intrusion probes, the intrusion cost at set sizes 4 and 8 were comparable to what we observed at set size 5; hence it is likely that the size of the intrusion cost at set size 5 is about the same regardless of whether set size is fixed or varies from trial to trial. The Discrete-State models would still have trouble in predicting a sufficiently large intrusion cost.

Conclusions

Our results challenge three broad classes of models of short-term recognition: Unidimensional Continuous-Strength models are challenged by serial-position curves of intrusion probes and new probes. This has already been demonstrated by Oberauer (2008), and the present experiments confirm the critical U-shaped serial-position effects on the accuracy of rejecting intrusion probes for visual materials. This challenge applies to all models in this class which assume that serial position effects are effects on memory strength (e.g.,Kahana & Sekuler, 2002; Mewhort & Johns, 2003; Nosofsky et al., 2011). Unidimensional Continuous-Strength models can escape this challenge by making alternative assumptions about serial-position effects. For instance, the resource model of Keshvari, van den Berg, and Ma (2013) could be applied to serial-position effects by assuming that objects in early and late list positions receive a larger resource share than those in the middle. In this model, a larger resource share translates into a higher precision of the representation, which facilitates acceptance of matching probes and rejection of mismatching probes. In its present version, the model of Keshvari et al. is not suited to account for intrusion costs, because it does not assume swap errors, and its decision process only compares each probe to the memory object in the probe's location – if the probe content matches a content bound to another location in the memory array, that has no effect on the model's behavior. Nevertheless, the assumption that serial position effects reflect differences in memory precision rather than memory strength is a potential way forward for Unidimensional Continuous-Strength models.

Discrete-State models – both unidimensional and Two-Dimensional variants – do well on the serial-position curves but have problems explaining the size of the intrusion cost. Discrete-State models of working memory provide limited options for explaining intrusion costs. We tried the two for which we found precedents in the literature: swap errors at encoding (Donkin et al., 2015) and failure to encode (or maintain) the context of an object (Cowan et al., 2013). There could be other theoretical options, but we were unable to think of one. For the time being, the size of the intrusion cost stands as a challenge for Discrete-State models of working memory.

Two-Dimensional Continuous-Strength models can explain the present findings well. Unfortunately, at present there is no model in this class that explains other benchmark phenomena of short-term recognition, such as the set-size effect on response speed (Sternberg, 1966; Donkin & Nosofsky, 2012) and accuracy (Donkin & Nosofsky, 2012; Luck & Vogel, 1998; Keshvari et al., 2013), and the serial-position effect, which we modelled here only in a descriptive way. One way forward could be to start from Unidimensional Continuous-Strength models that have been successful in explaining some of these benchmarks – such as the Variable Precision model of Keshvari et al. (2013) – and extend them into Two-Dimensional models so that they can account for intrusion costs. Another way forward could be to augment existing Two-Dimensional Continuous-Strength models such as the one developed here (cf. Göthe & Oberauer, 2008; Oberauer & Lange, 2009) with mechanisms that enable them to explain set-size effects and serial-position effects, such as a resource limit on memory strength (Keshvari, van den Berg, & Ma, 2013; Schneegans & Bays, 2017; van den Berg et al., 2012), or interference between memory representations (Oberauer & Lin, 2017).

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Footnotes

[1]In the literature on visual working memory, the conjunction of one or more features with a location is often referred to as an object. Because our experiments use visual materials presented in different locations, we will use the term object to refer to a representation of the conjunction of visual features with their location. We use the term item to refer to the object's content (i.e., its visual features) and location to refer to its temporal-spatial context.

[2]This simple representation is sufficient for our purpose. When objects consist of multiple visual features (e.g., color and shape), and memory for their conjunction is of interest, the model would have to be extended to include multiple content features.

[3]In Oberauer (2008), if the location cannot be retrieved in case of the new probe, the $M(probe_{context}, l)$ is set to -1, and the memory strength $w_l = 1$.

[4]Because the experiments in the study have constant set size, the normalization does not affect the prediction of the Continuous models, and we introduced it only for mathematical convenience. When the model is applied to experiments with variations of set sizes, the normalization makes the model behave like a resource model in which each object's strength directly reflects its resource share.

Tables

Table 1

Parameters used for simulating model predictions.

Parameter	Unidimensional Discrete-State Model	Two-Dimensional Discrete-State Model	Unidimensional Continuous-Strength Model	Two-Dimensional Continuous-Strength Model
m_p	0.8	0.7	–	–
m_r	0.8	0.7	–	–
d_m	1.0	1.0	–	–
w_p	–	–	0.75	0.5
w_r	–	–	0.75	0.5
d_w	–	–	1.0	1.0
s	2.0	–	–	–
b	0.8	–	–	–
b_p	–	0.3	–	–
b_r	–	0.3	–	–
d_b	–	1.0	–	–
k	5.0	3.0	–	–
g	0.3	0.2	–	–
g_{plus}	–	0.9	–	–
c	–	–	2.5	–
u	–	–	0.2	–
λ	–	–	20.0	6.75
τ	–	–	0.25	0.15
d	–	–	–	0.5
m	–	–	–	0.15

Table 2

Summary of statistics for all the experiments.

Experiment	Model	Bayes factor
Exp 1		
	Comparing to $PC \sim ID$	
	$PC \sim ProbeType + ID$	388.44
	$PC \sim SerialPosition + ID$	1.55e+8
	$PC \sim ProbeType + SerialPosition + ID$	3.49e+12
	$PC \sim ProbeType \times SerialPosition + ID$	6.01e+14
	Comparing to $PC \sim SerialPosition + ID$	
	$PC \sim SerialPosition + SerialPosition^2 + ID$	
	Positive	30
	New	47659
	Intrusion	2.28e+8
	Comparing to $PC \sim PositionofOrigin + ID$	
	$PC \sim PositionofOrigin + PositionofOrigin^2 + ID$	191.05
Exp 2		
	Comparing to $PC \sim ID$	
	$PC \sim ProbeType + ID$	1.75e+26
	$PC \sim SerialPosition + ID$	1403.3
	$PC \sim ProbeType + SerialPosition + ID$	9.75e+32
	$PC \sim ProbeType \times SerialPosition + ID$	2.8e+41
	Comparing to $PC \sim SerialPosition + ID$	
	$PC \sim SerialPosition + SerialPosition^2 + ID$	
	Positive	19202
	New	0.33
	Intrusion	4.74
	Comparing to $PC \sim PositionofOrigin + ID$	
	$PC \sim PositionofOrigin + PositionofOrigin^2 + ID$	23.28
Exp 3		
	Comparing to $PC \sim ID$	
	$PC \sim ProbeType + ID$	1.59e+5
	$PC \sim SerialPosition + ID$	359.19
	$PC \sim ProbeType + SerialPosition + ID$	1.4e+8
	$PC \sim ProbeType \times SerialPosition + ID$	1.17e+9
	Comparing to $PC \sim SerialPosition + ID$	
	$PC \sim SerialPosition + SerialPosition^2 + ID$	
	Positive	19202
	New	0.33
	Intrusion	4.74
	Comparing to $PC \sim PositionofOrigin + ID$	
	$PC \sim PositionofOrigin + PositionofOrigin^2 + ID$	3.35

Note: PC = proportion correct, ID = subject random effect

Table 3

Goodness-of-fit for Unidimensional Discrete-State model, Two-Dimensional Discrete-State model, and Two-Dimensional Continuous-Strength Model. The Δ LL and Δ AIC represent the difference between each model's –LL and AIC and the lowest values of any model in the experiment, averaged over participants; smaller values reflect better fit.

Experiment	Model	Δ-LL	ΔAIC
Experiment 1			
	Unidimensional Discrete-State model	38.13	74.26
	Two-Dimensional Discrete-State model	15	34
	Unidimensional Continuous-Strength model	22.34	44.68
	Two-Dimensional Continuous-Strength model	0	0
Experiment 2			
	Unidimensional Discrete-State model	13.14	24.28
	Two-Dimensional Discrete-State model	9.74	23.48
	Unidimensional Continuous-Strength model	12.43	24.86
	Two-Dimensional Continuous-Strength model	0	0
Experiment 3			
	Unidimensional Discrete-State model	20.93	39.86
	Two-Dimensional Discrete-State model	15.17	34.34
	Unidimensional Continuous-Strength model	14.68	29.35
	Two-Dimensional Continuous-Strength model	0	0

Table 4

Parameters estimated from fitting the models to the experiments data. The numbers outside of the parentheses are the averages of the parameters across the experiments, and the numbers in parentheses are the standard deviance of the parameters.

Parameter	Unidimensional Discrete-State Model	Two-Dimensional Discrete-State Model	Unidimensional Continuous-Strength Model	Two-Dimensional Continuous-Strength Model
m_p	0.62(0.34)	0.55(0.30)	–	–
m_r	0.52(0.23)	0.71(0.22)	–	–
d_m	1.99(3.84)	3.60(5.91)	–	–
w_p	–	–	0.58(0.40)	0.53(0.36)
w_r	–	–	0.55(0.28)	0.37(0.22)
d_w	–	–	1.68(3.88)	1.27(3.62)
s	0.68(0.32)	–	–	–
b	0.12(0.18)	–	–	–
b_p	–	0.43(0.28)	–	–
b_r	–	0.45(0.19)	–	–
d_b	–	3.70(5.06)	–	–
k	2.21(0.94)	0.57(0.25)	–	–
g	0.49(0.23)	0.33(0.17)	–	–
g_{plus}	–	0.79(0.20)	–	–
c	–	–	14.30(6.02)	–
u	–	–	0.68(0.25)	–
λ	–	–	14.25(4.51)	7.09(2.88)
τ	–	–	0.16(0.10)	0.38(0.88)
d	–	–	–	0.42(0.30)
m	–	–	–	0.17(0.14)

Figures

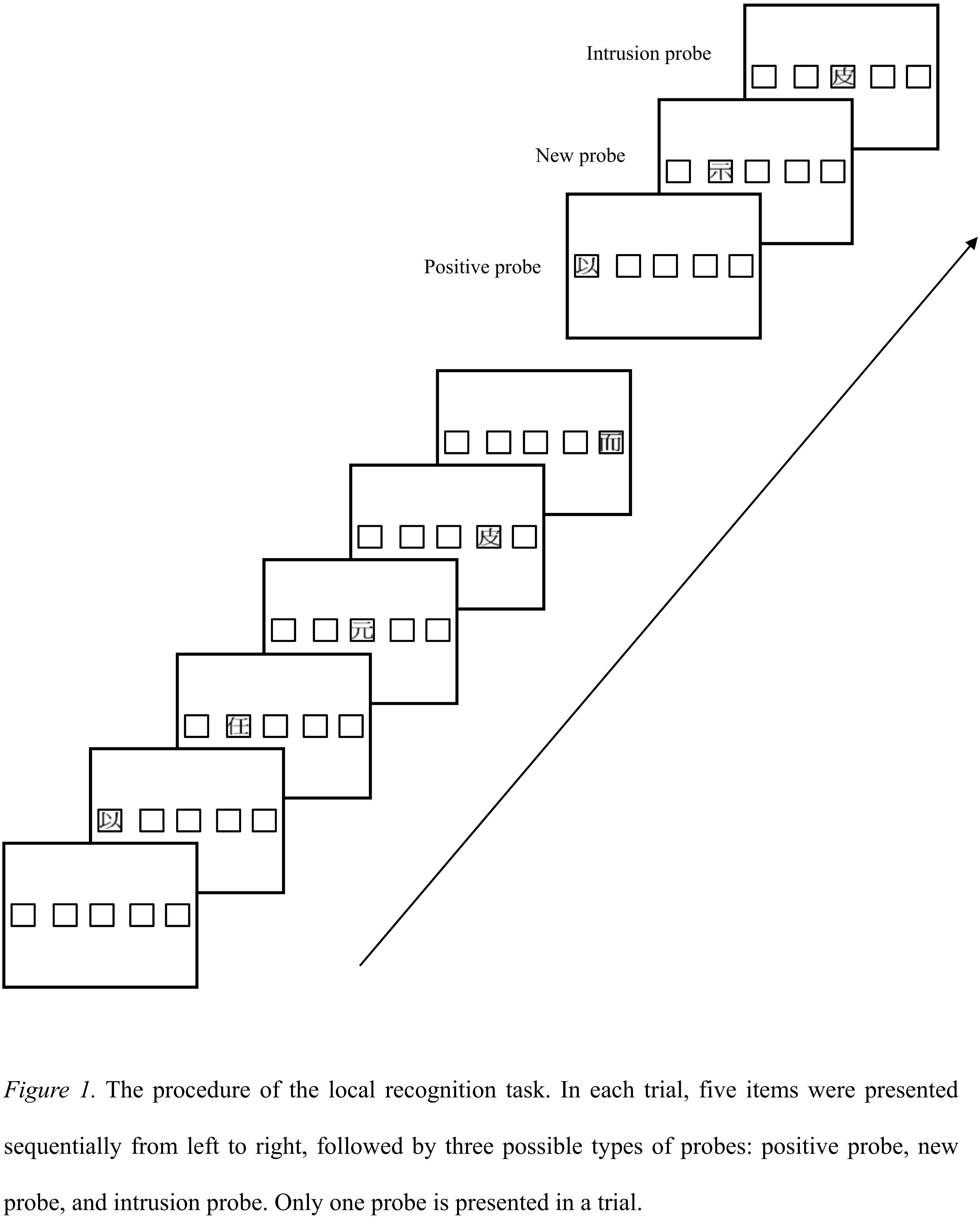

Figure 1. The procedure of the local recognition task. In each trial, five items were presented sequentially from left to right, followed by three possible types of probes: positive probe, new probe, and intrusion probe. Only one probe is presented in a trial.

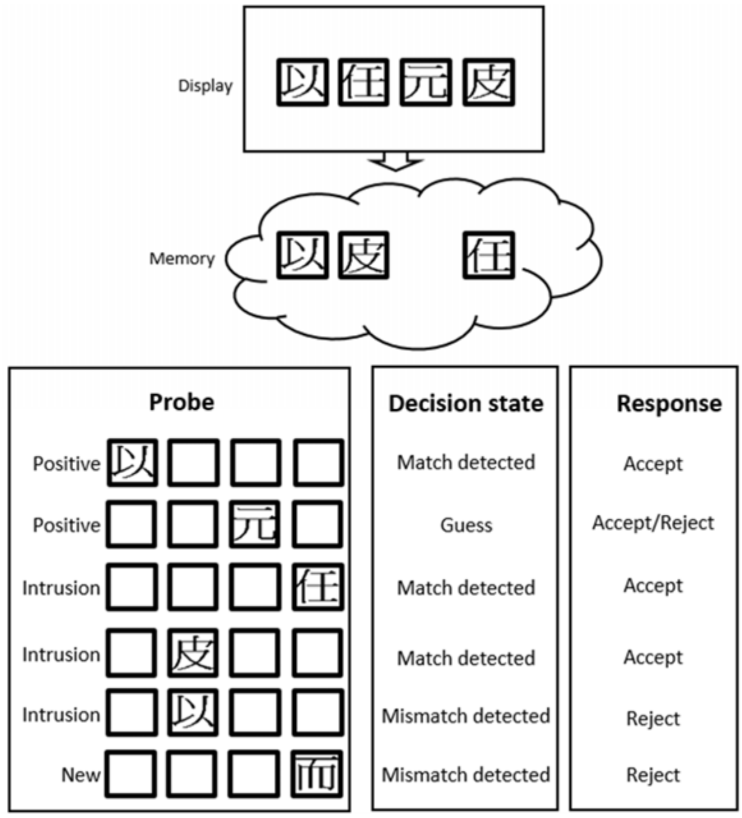

Figure 2. The illustration of the Unidimensional Discrete-State model. In the illustration, the first object is remembered with its correct content. The second object is remembered with the wrong content (i.e., the content from the first location). The third object is not stored, and the fourth object is remembered with the content from the third location.

Probe	Having object i in memory	Having correct binding	Swap error occurred between target and probe	Probe is compared to	Response
Positive $p_{i,i}$	$Pm(i)$	$B(i)$		$p_{i,i}$	Correctly accept the probe
		$1 - B(i)$		$p_{i,j}; j \neq i$	Incorrectly reject the probe
	$1 - Pm(i)$			$-$	Random guess
New $p_{x,i}$	$Pm(i)$	$B(i)$		$p_{i,i}$	Correctly reject the probe
		$1 - B(i)$		$p_{i,j}; j \neq i$	Incorrectly reject the probe
	$1 - Pm(i)$			$-$	Random guess
Intrusion $p_{i,j}$	$Pm(i)$	$B(i)$		$p_{i,i}$	Correctly reject the probe
		$1 - Pb(i)$	$Pm(j) * Ps(i,j)$	$p_{j,i}$	Incorrectly accept the probe
			$1 - Pm(j) * Ps(i,j)$	$p_{k,i}; k \neq i,j$	Incorrectly reject the probe
	$1 - Pm(i)$			$-$	Random guess

Figure 3. Multinomial process trees of the recognition process of the Unidimensional Discrete-State model. $B(i)$ represents the probability of having correct binding at object i, which is $1 - \sum_{j \neq i} Ps(i,j) \cdot Pm(j)$.

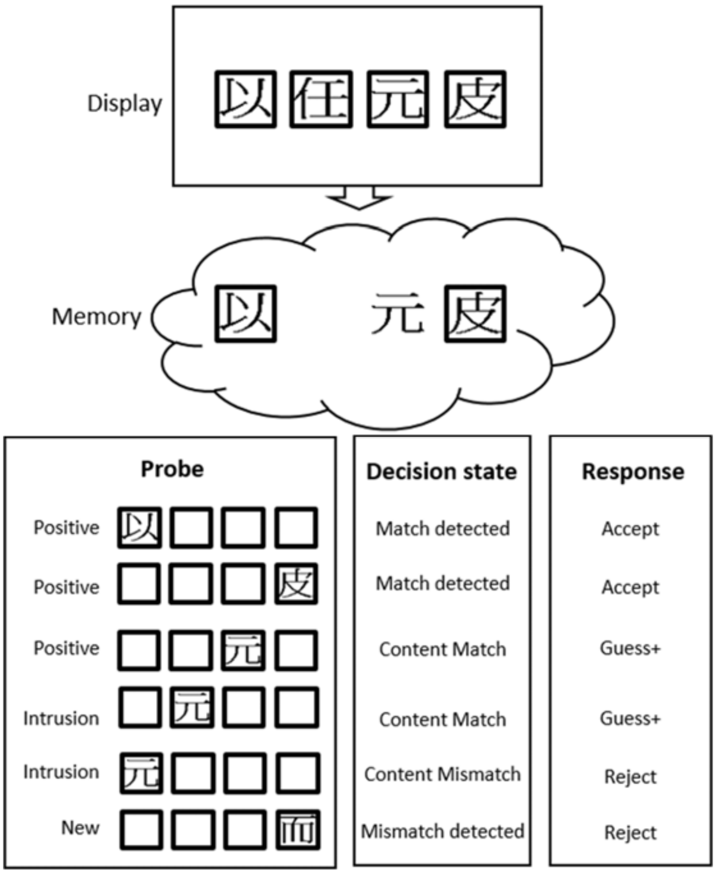

Figure 4. Illustration of the Two-Dimensional Discrete-State model. In the illustration, the first and the fourth objects are remembered with their context feature. The second object is not remembered at all. The third object is remembered without context feature.

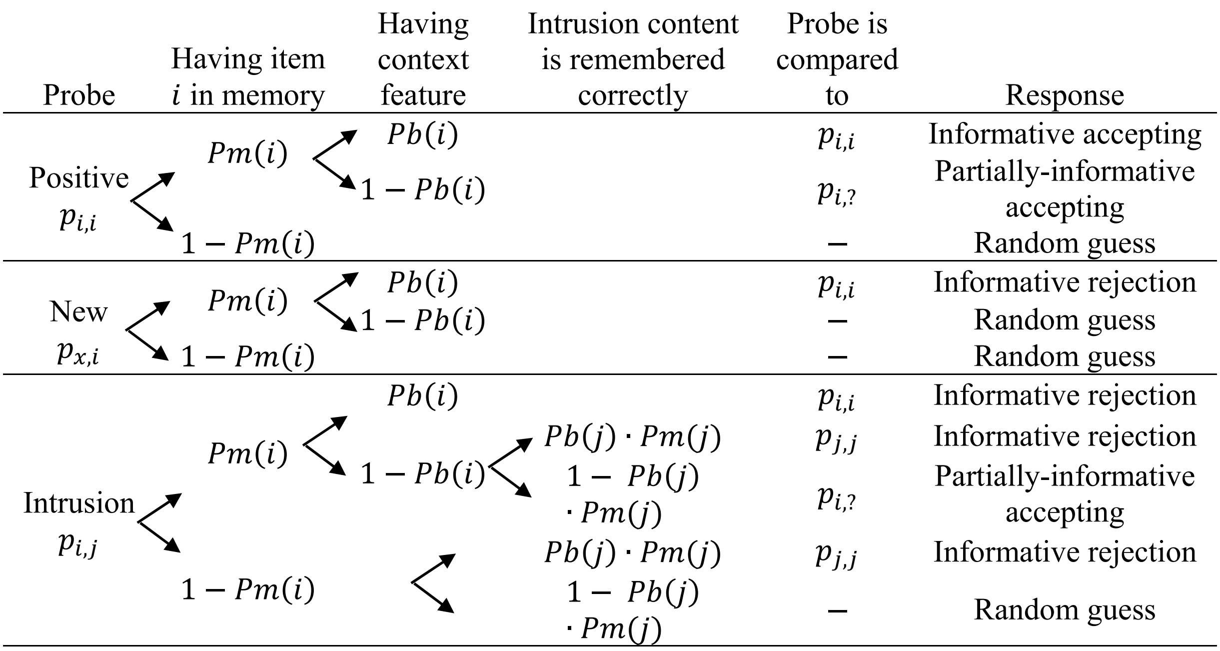

Figure 5. Multinomial processing trees of the recognition process of the Two-Dimensional Discrete-State model.

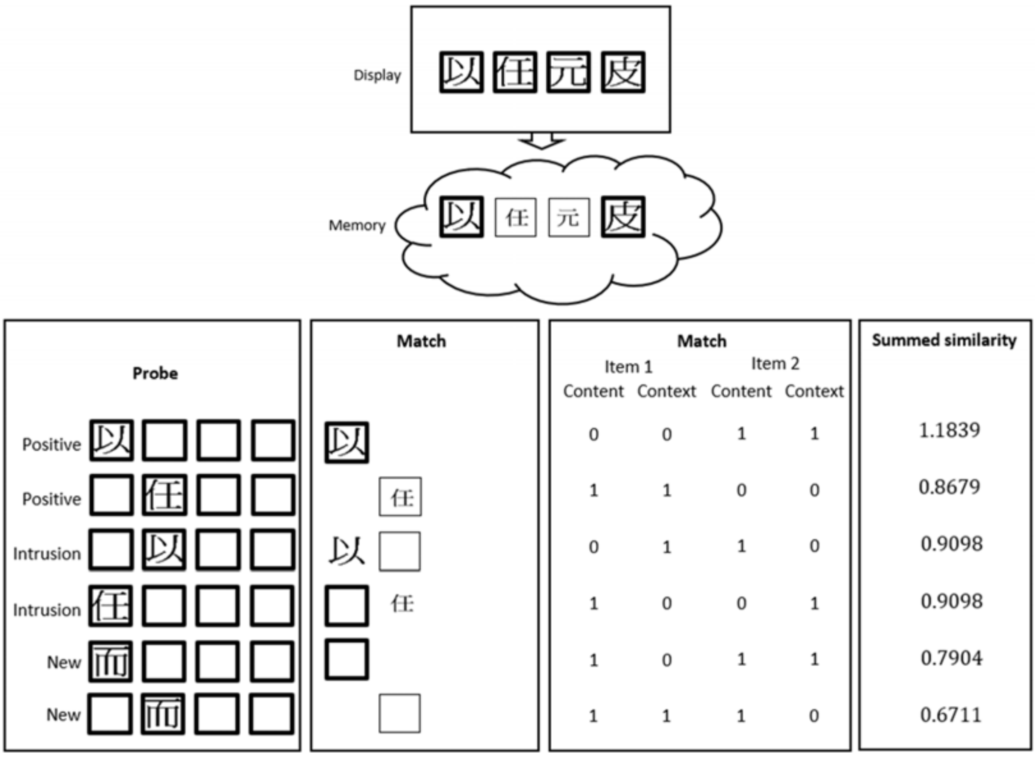

Figure 6. Illustration of the Unidimensional Continuous-Strength model. In the illustration, all the items are remembered with variable strength. The size of the Chinese character indicates the strength of content memory, and the thickness of the frame represents the strength of context memory. The Match values are the $D_{content}(i,j)$ and $D_{context}(i,j)$ values entering Equation 7, for items i = 1 and 2. The summed similarity is calculated by Equations 7 and 8 with $w_1 = 1.0, w_2 = 0.5, c = 1, u = 0.5$.

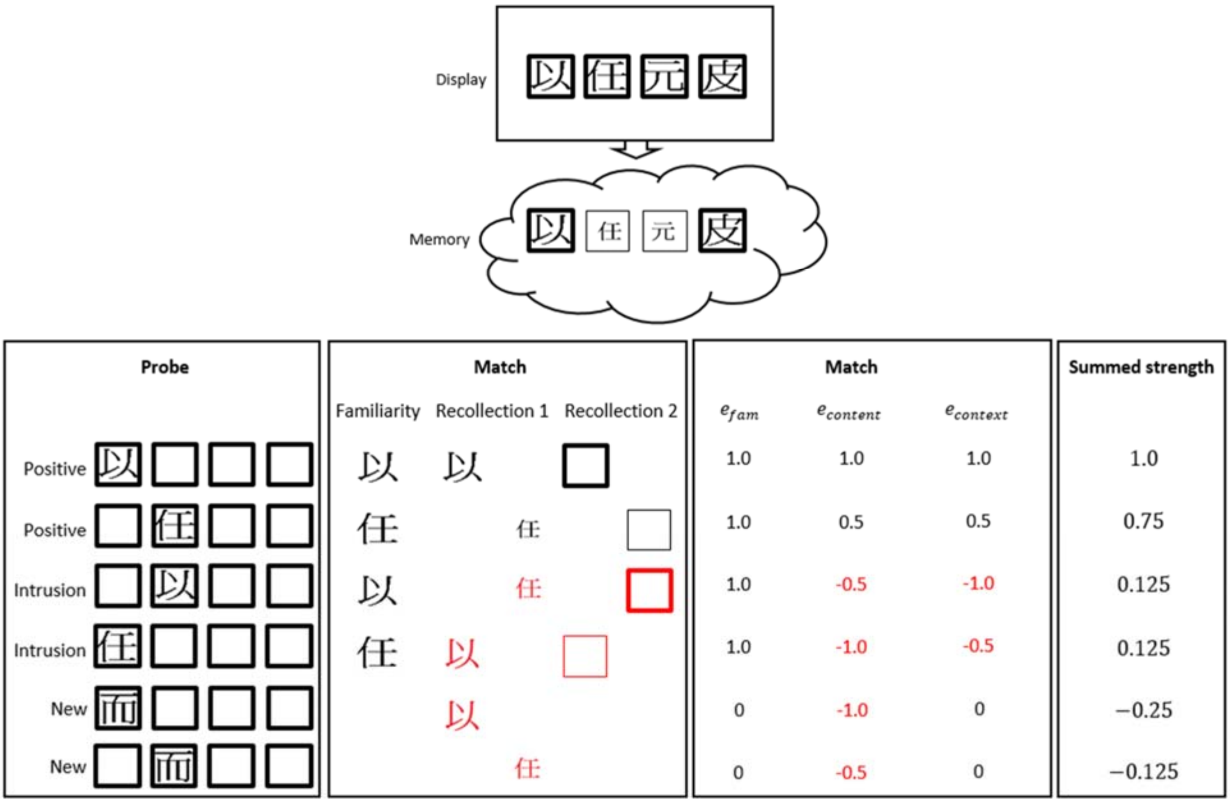

Figure 7. Illustration of the Two-Dimensional Continuous-Strength model. All the items are remembered with variable strength. The size of the Chinese character indicates the strength of content memory, and the thickness of the frame represents the strength of context memory. Black color represents the retrieved context and content providing evidence for accepting the probe, whereas red color indicates the retrieved context and content providing evidence for rejecting the probe. The summed strength is calculated through Equations 10 to 13 with $m = 0.5, d = 0.5, w_1 = 1, w_2 = 0.5$.

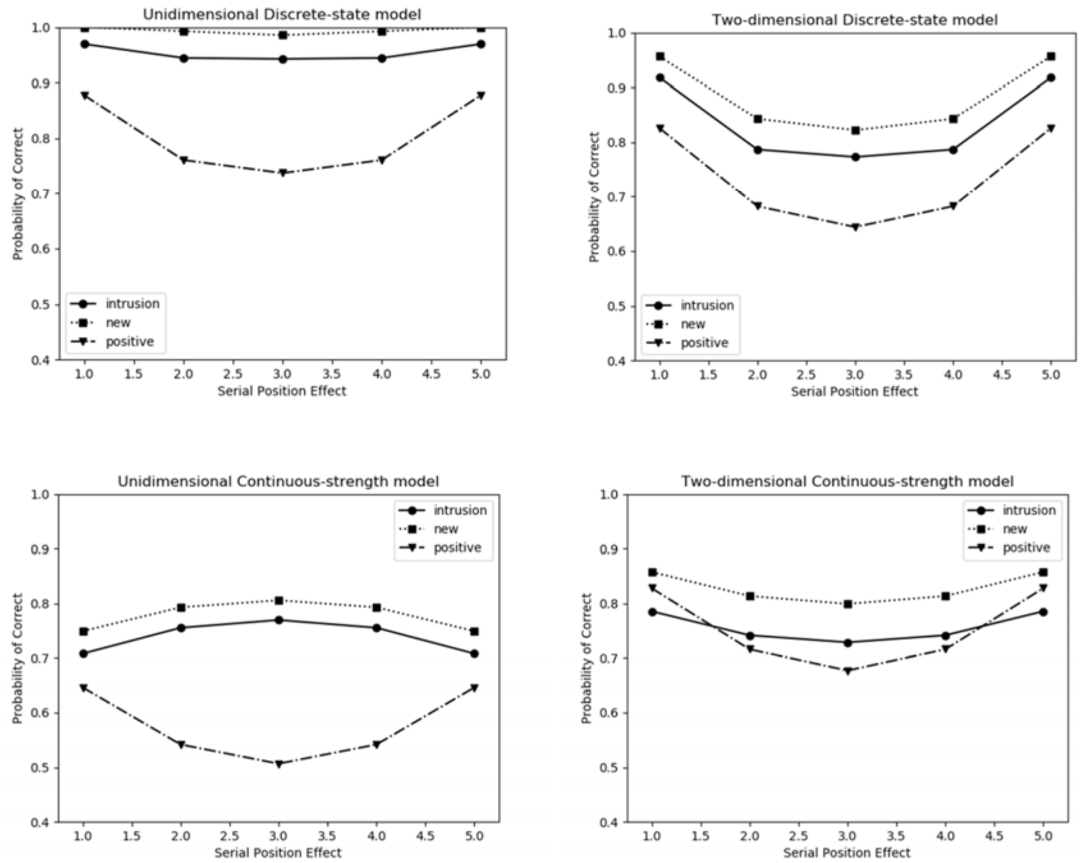

Figure 8. The serial-position effect in local recognition task predicted by the four models.

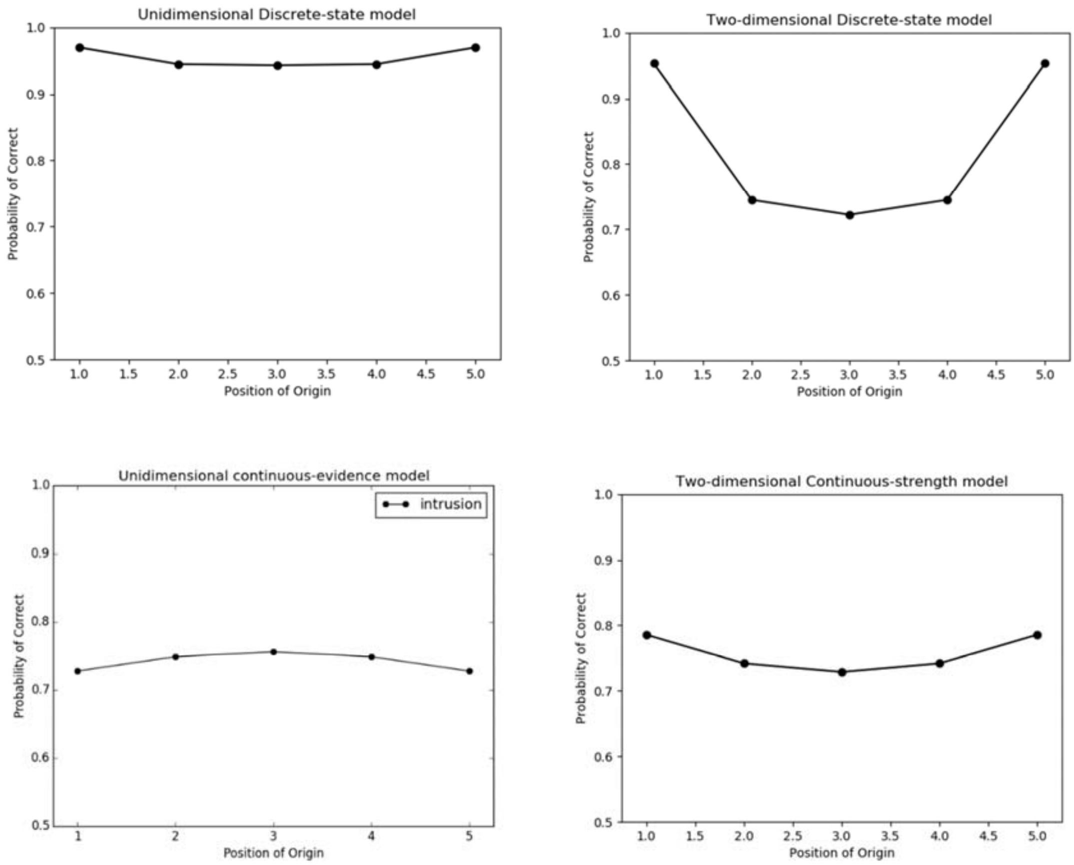

Figure 9. The position-of-origin effect in local recognition task predicted by the four models.

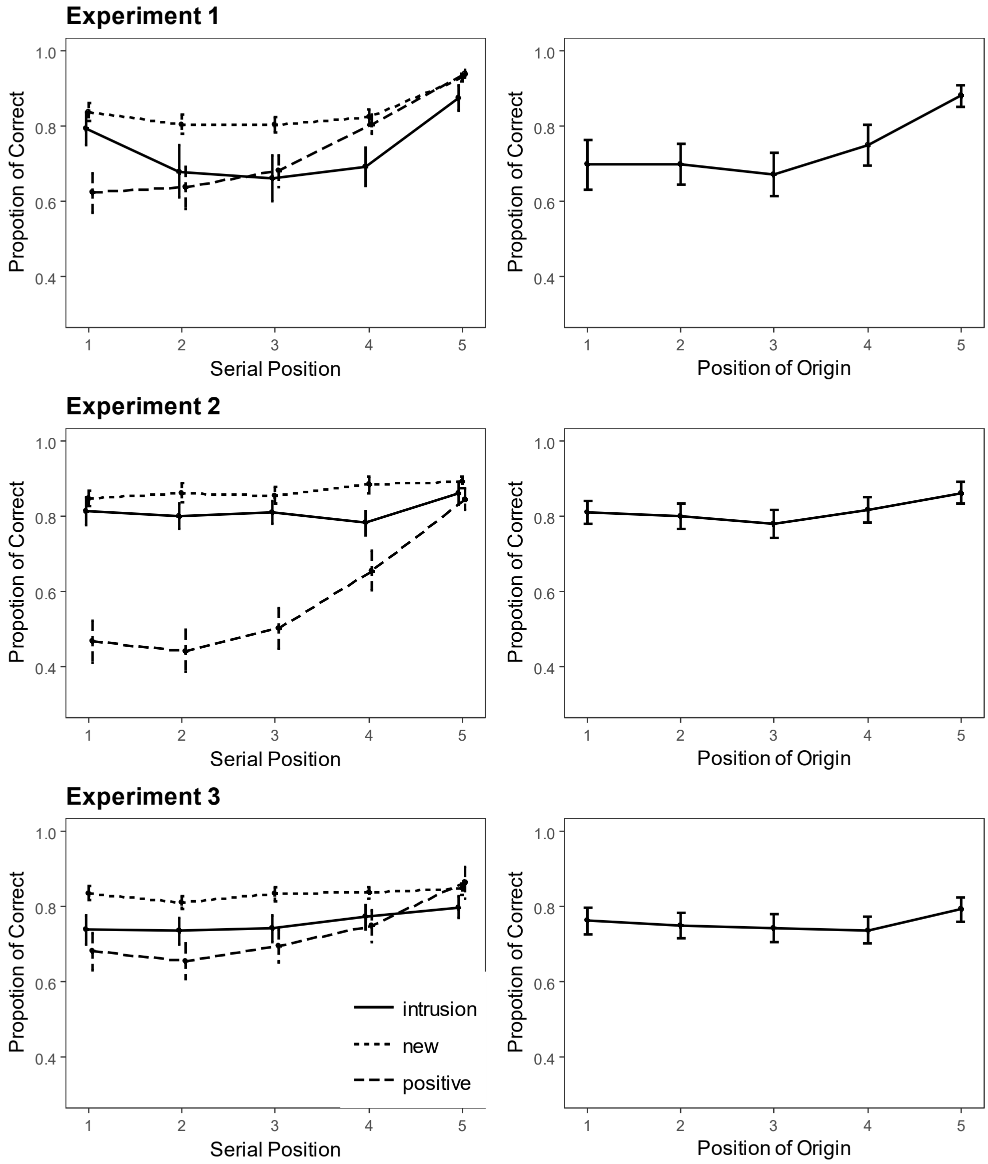

Figure 10. The serial-position effect of Experiment 1 (top left), Experiment 2 (middle left), and Experiment 3 (bottom left), and the position-of-origin effects of Experiment 1 (top right), Experiment 2 (middle right), and Experiment 3 (bottom right).

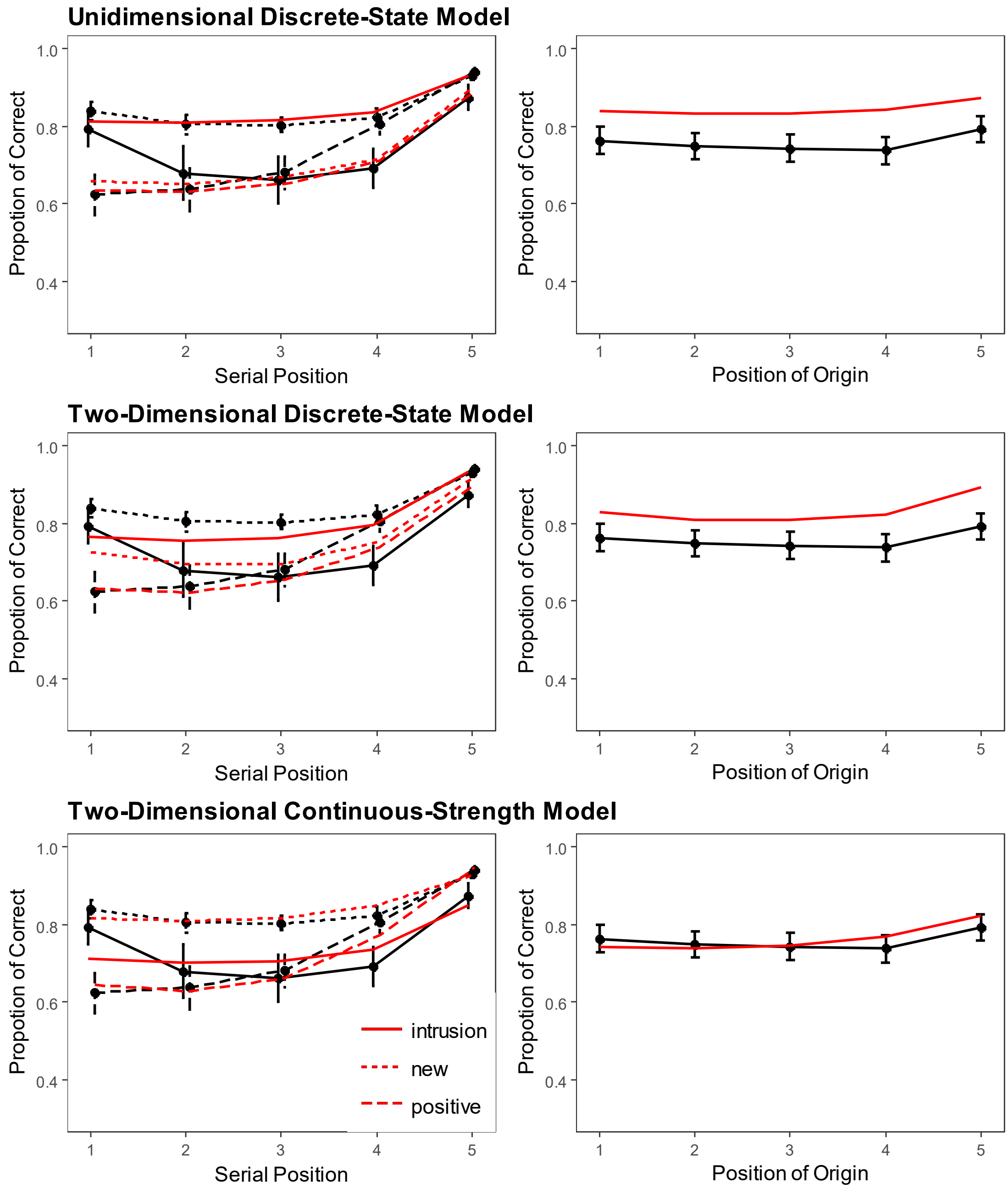

Figure 11. The predicted serial-position effect and position of origin for Experiment 1. The black lines are observed from the data, and the red lines are model predictions. The top figures are the predictions from the Unidimensional Discrete-State model. The middle figures are the predictions from the Two-Dimensional Discrete-State model. The bottom figures are the predictions from the Two-Dimensional Continuous-Strength model.

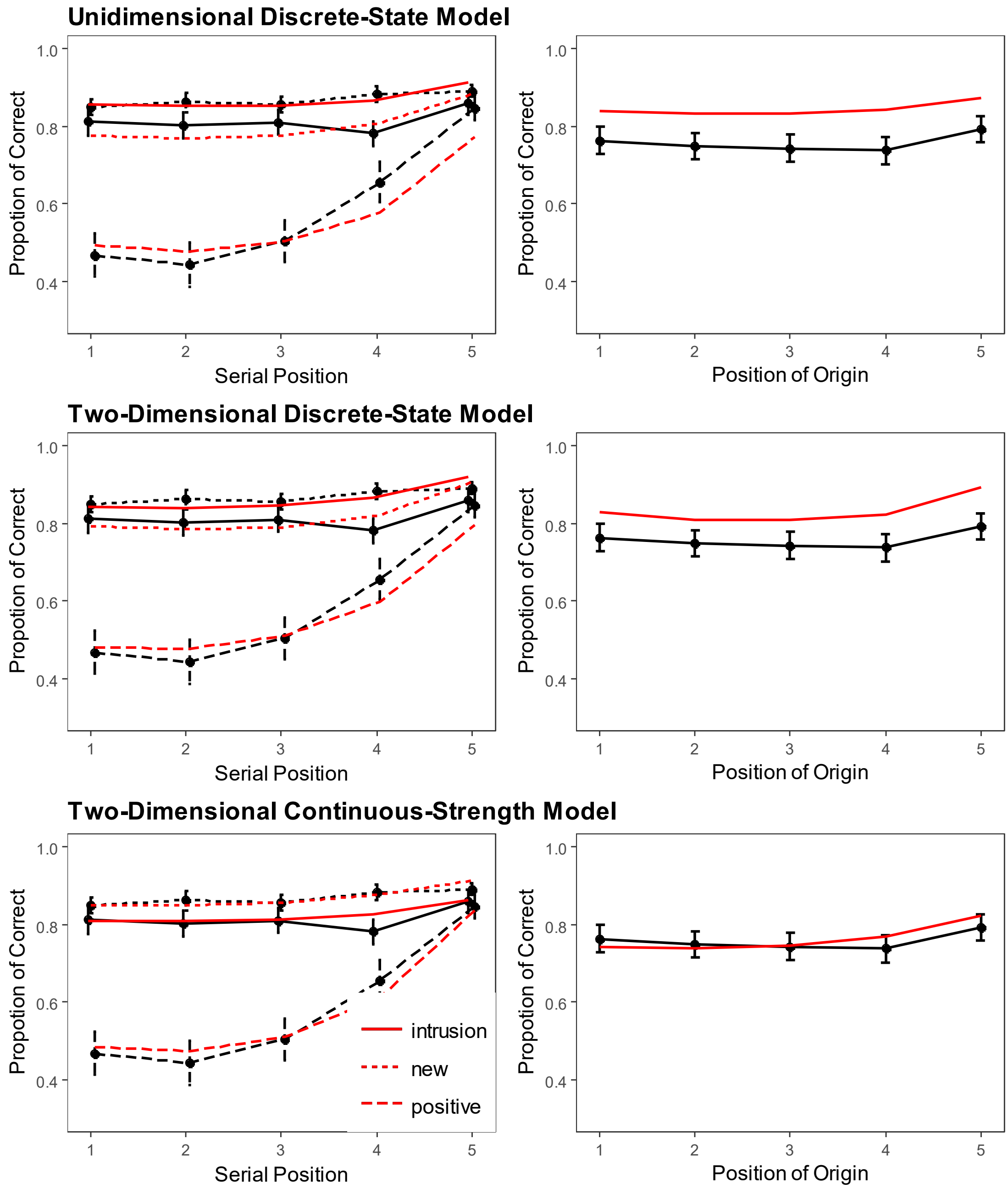

Figure 12. The predicted serial-position effect and position of origin for Experiment 2. The black lines are observed from the data, and the red lines are model predictions. The top figures are the predictions from the Unidimensional Discrete-State model. The middle figures are the predictions from the Two-Dimensional Discrete-State model. The bottom figures are the predictions from the Two-Dimensional Continuous-Strength model

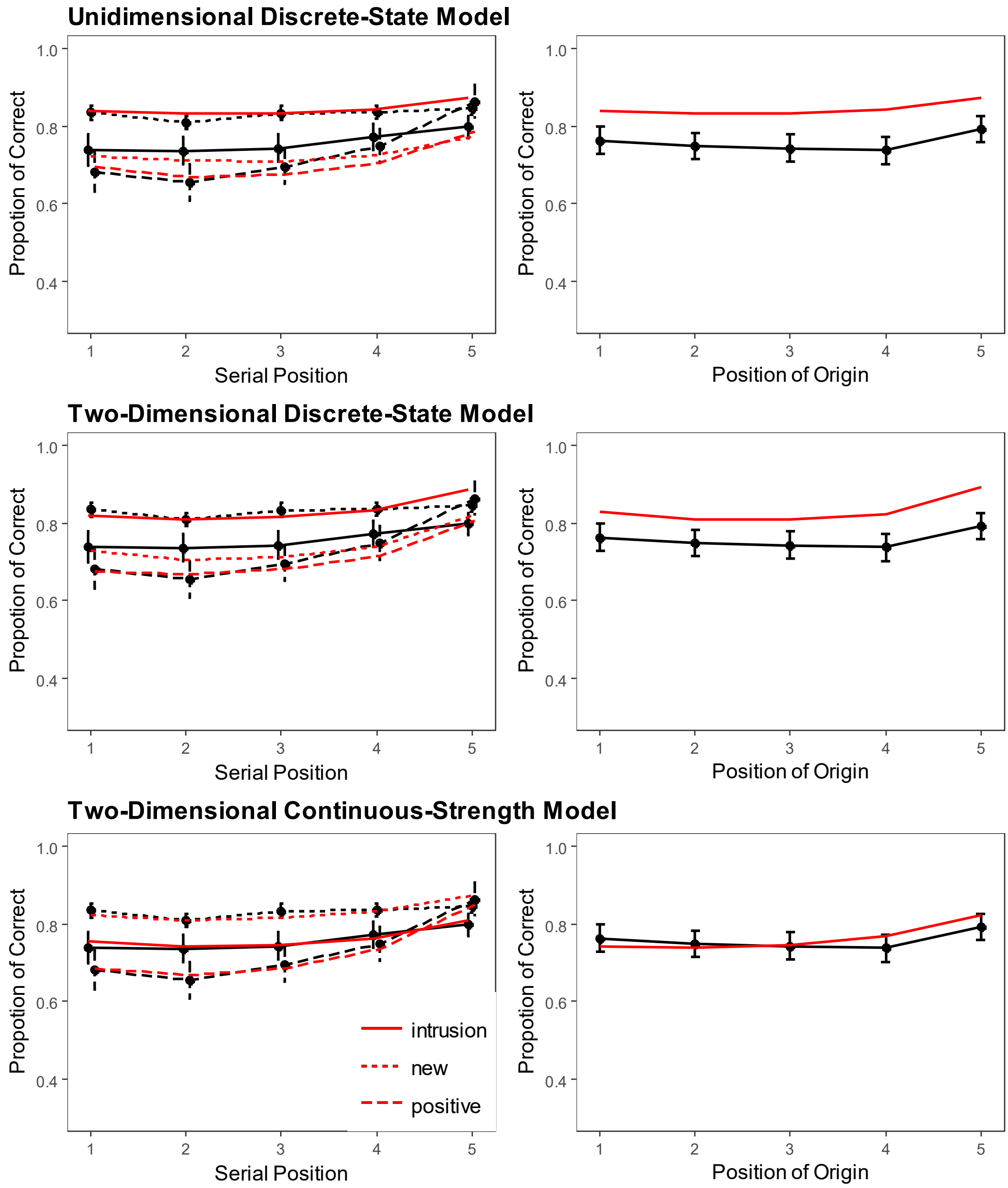

Figure 13. The predicted serial-position effect and position of origin for Experiment 3. The black lines are observed from the data, and the red lines are model predictions. The top figures are the predictions from the Unidimensional Discrete-State model. The middle figures are the predictions from the Two-Dimensional Discrete-State model. The bottom figures are the predictions from the Two-Dimensional Continuous-Strength model

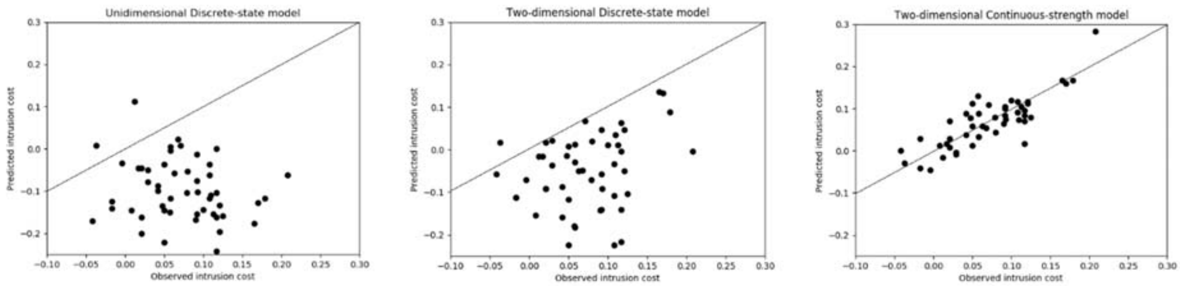

Figure 14. The observed intrusion costs and the predicted intrusion costs from the Unidimensional Discrete-State model (left), Two-Dimensional Discrete-State model (middle), and Two-Dimensional Continuous-Strength model (right). Each data point reflects the intrusion cost (i.e., accuracy on new probes minus accuracy on intrusion probes) of one participant in one of the three experiments.

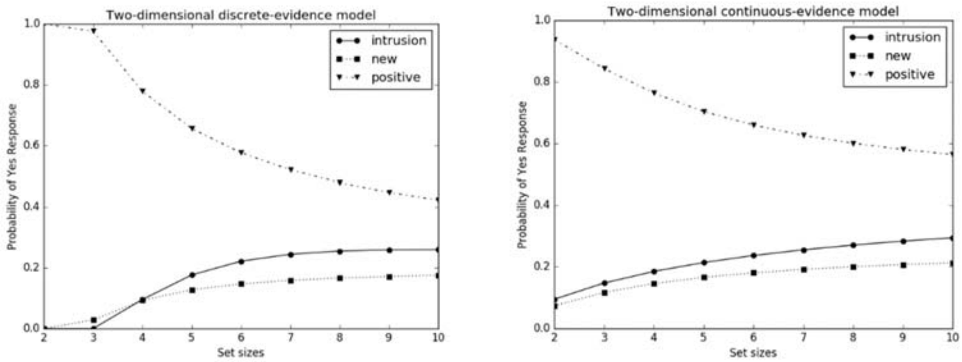

Figure 15. The set-size effect predicted by Two-Dimensional Discrete-State model (left) and Two-Dimensional Continuous-Strength model (right).